Improvements on Coronal Hole Detection using Supervised Classification

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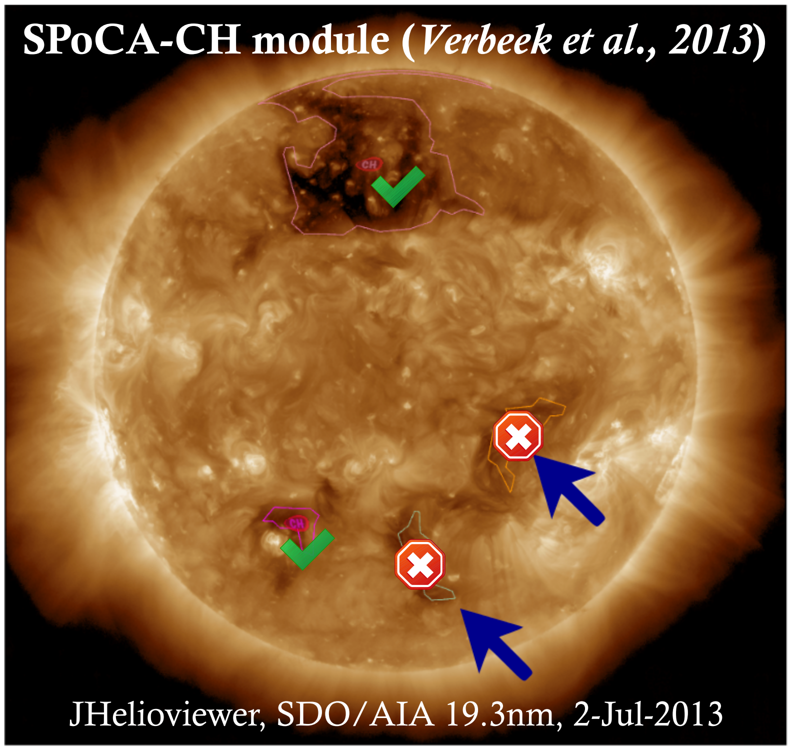
Problem Statement

- It is difficult to study coronal holes in SDO/AIA images of the Sun in a consistent manner because they evolve in space and time, and are easily confused with filament channels.



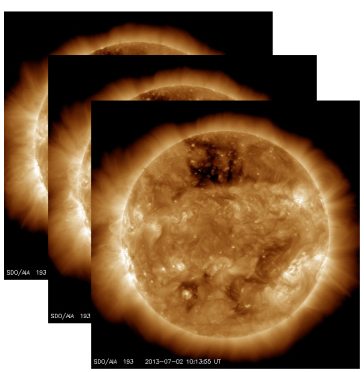
Error: ~15%

Work Approach

I. Data Preparation

We use the SPoCA-CH module (*Verbeek et al., 2013)* and prepare training sets of manually labeled *'coronal holes'* and *'filament channels'*.

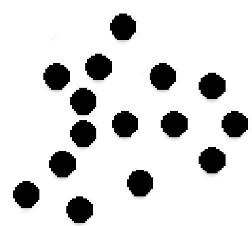
1. SDO/AIA images:



SDO/AIA Fe XII 19.3nm

SPoCA →

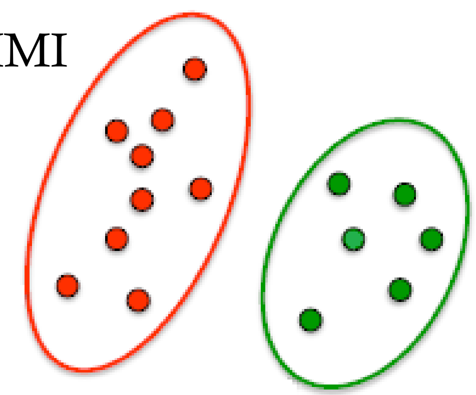
2. CH Candidates:



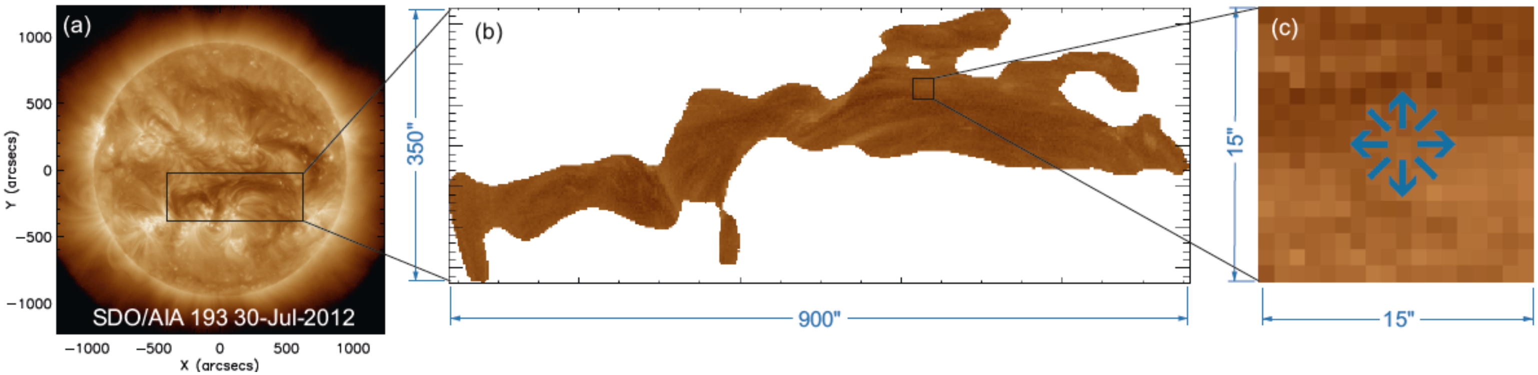
→ SDO/HMI

→ Hα

3. Training Sets:



II. Attributes

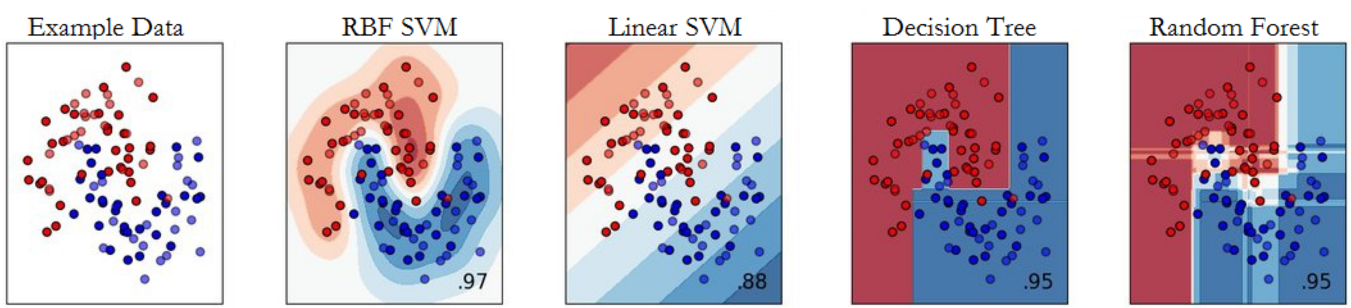


Reiss et al., (2015)

- We study a set of decisive attributes including *shape measures*, *magnetic flux properties*, and *first- and second-order image statistics*.

III. Supervised Classification

- The attributes are used as input for *supervised classification algorithms* to design a suitable decision rule.



Classifier Comparison (www.scikit-learn.org)

Classifier Performance

$$\mathrm{TSS} = \underbrace{\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}}_{\textbf{TPR}} - \underbrace{\frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}}}_{\textbf{FPR}}$$

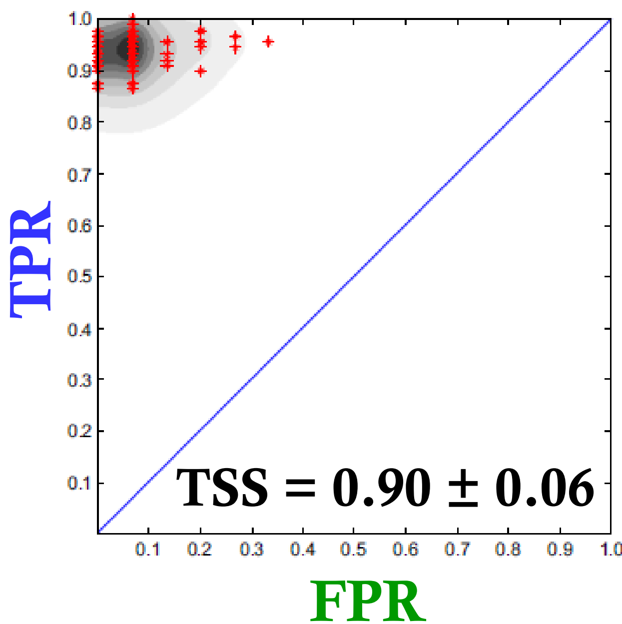
TPR: Proportion of correctly predicted CHs among all CHs

FPR: Proportion of FCs that were classified as CHs among all FCs

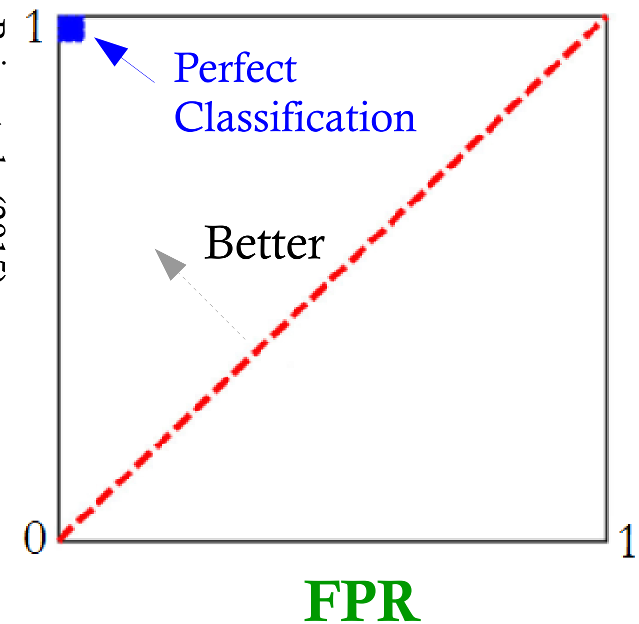
Example:

- **Time range [years]:** 2011 – 2013
- **Location:** ± 30° in lon/lat
- **Imbalance:** 252 CHs and 46 FCs

Linear SVM



Reiss et al., (2015)



Conclusion

1. We developed a new approach for the detection of coronal holes based on machine learning.
2. We find that all classifiers (*SVM*, *Linear SVM*, *Decision Tree*, and *Random Forest*) show good results (TSS ~ 0.90) (full-disk: TSS ~ 0.80).
3. Including magnetic field information systematically improves the performance.
4. We conclude that the developed approach is useful for a wide range of imaging data in solar physics.

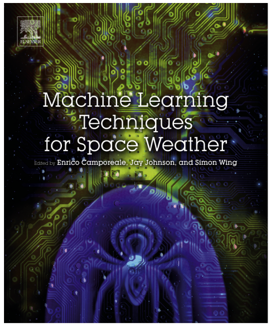
Further Reading

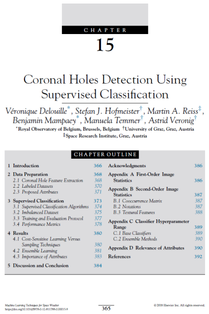
- Related References:

Reiss, M.A. et al. **Improvements on coronal hole detection in SDO/AIA images using supervised classification,** J. Space Weather Space Clim. 5, A23 (2015).


Improvements on coronal hole detection in SDO/AIA images using supervised classification

Delouille, V. et al. **Chapter 15 - Coronal Holes Detection Using Supervised Classification in Machine Learning Techniques for Space Weather,** 365–395 (Elsevier, 2018).




CHAPTER
15
Coronal Holes Detection Using Supervised Classification

CHAPTER OUTLINE

- Source Code:

https://bitbucket.org/vdelouille/coronal_hole_detection_ml

- Contact Details:

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More on:
Feature Selection,
Class Imbalance, etc.